Temperature Downscaling in High Spatial Resolution Land Surface Modeling in Support of US Drought Monitoring Efforts

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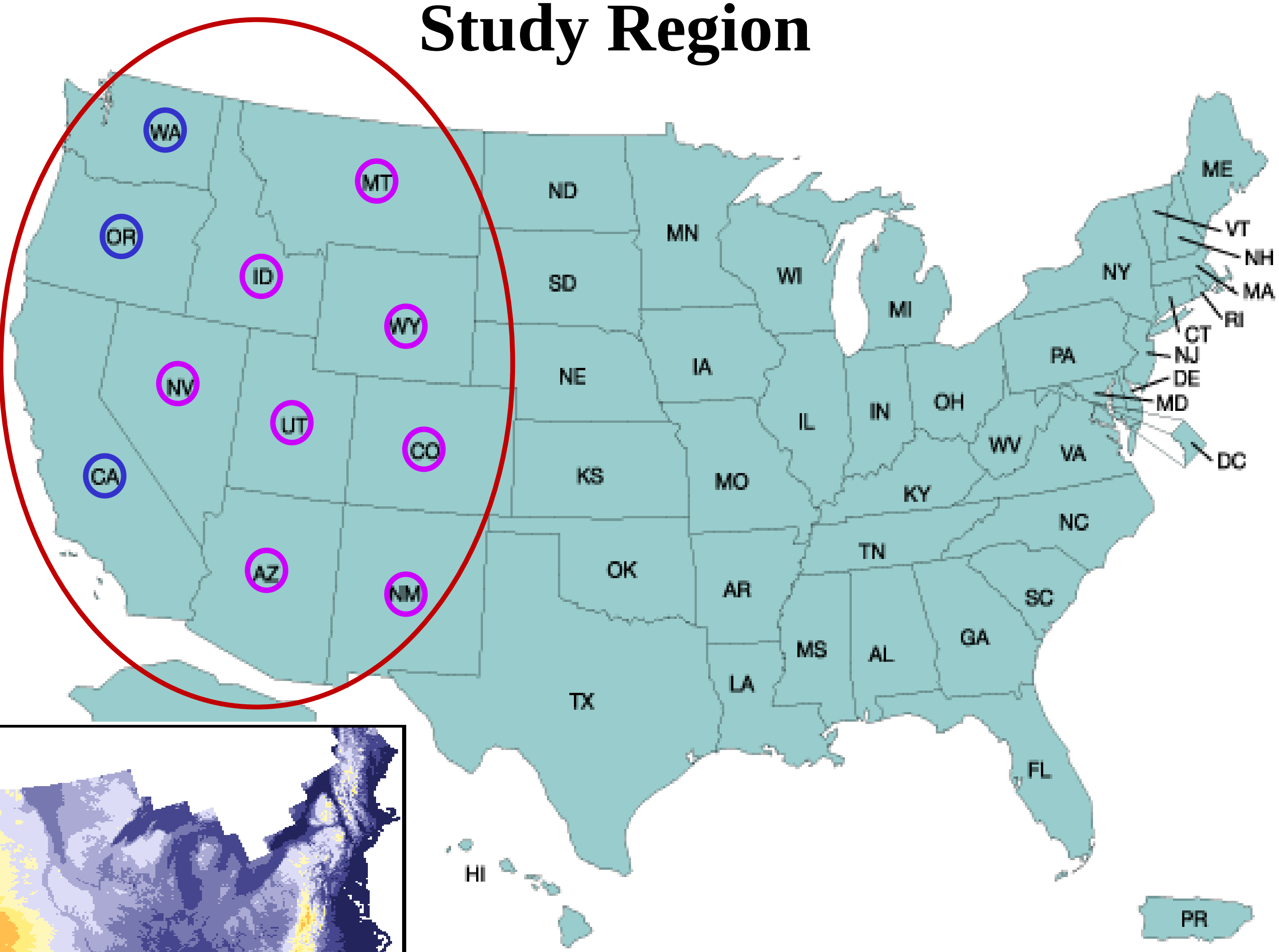
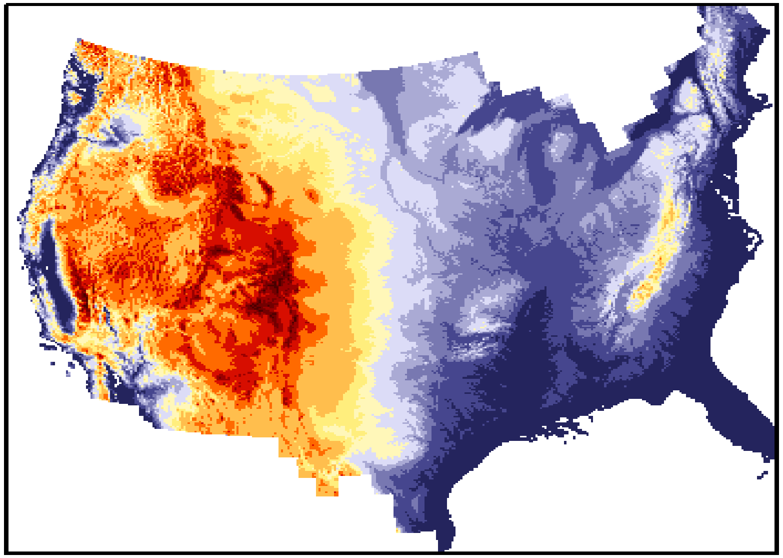
Motivations

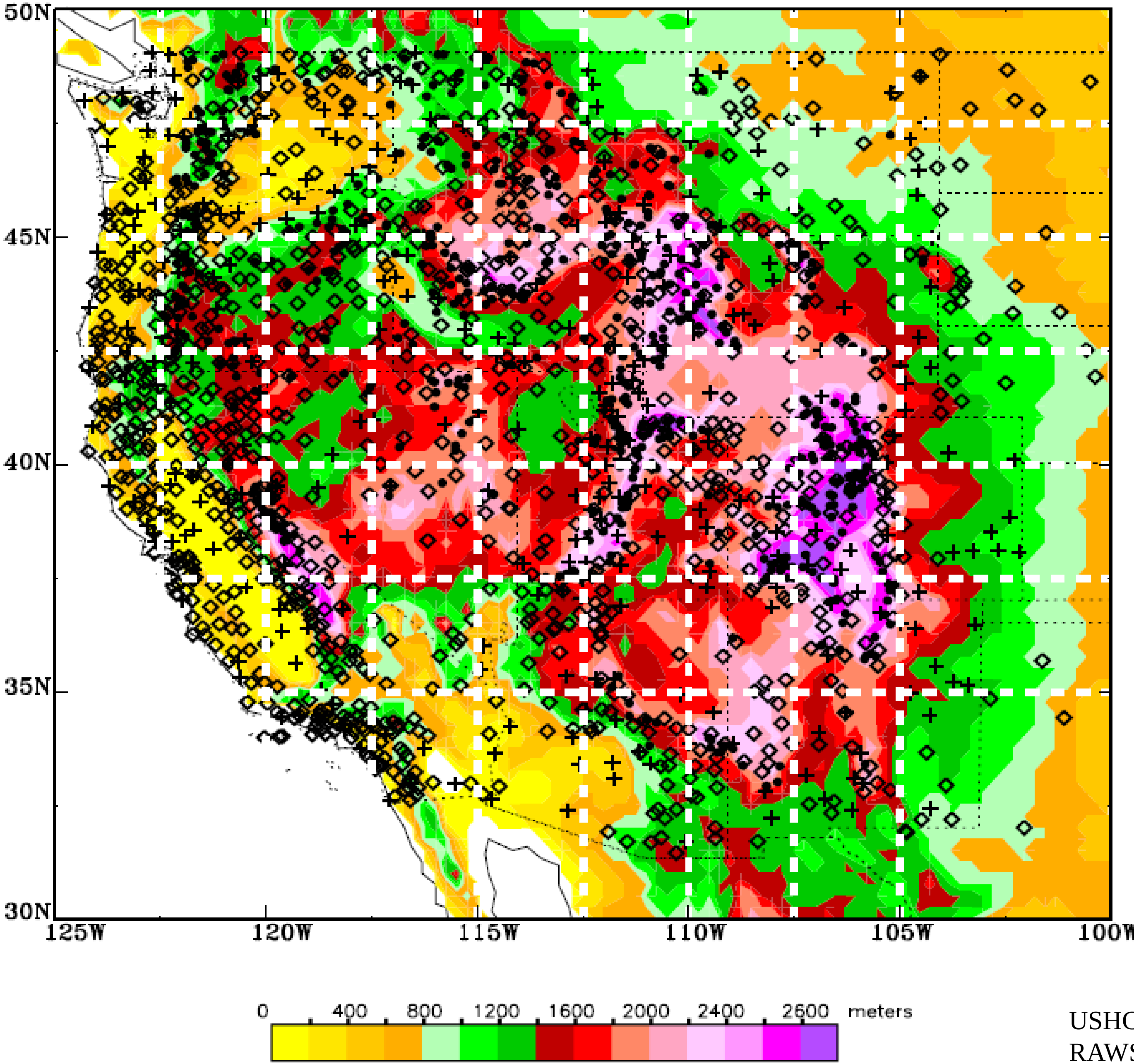
- Land surface processes influence weather and climate by regulating the partitioning of surface water and energy exchanges.
- Accurate forcing data at high spatial resolution are essential for reliable land surface and hydrological modeling to better match land surface complexity.
- The constant free-air lapse rate (-6.5^{o}C/KM) has been widely applied in land surface modeling to downscale air temperature and other related forcing variables.
- However, near surface lapse rates vary spatially and temporally due to the complex terrain, and new lapse rates are required to characterize these variations.

Study Region





Distribution of in-situ stations



Data:

Daily observations of maximum, minimum, and mean air temperature

FROM

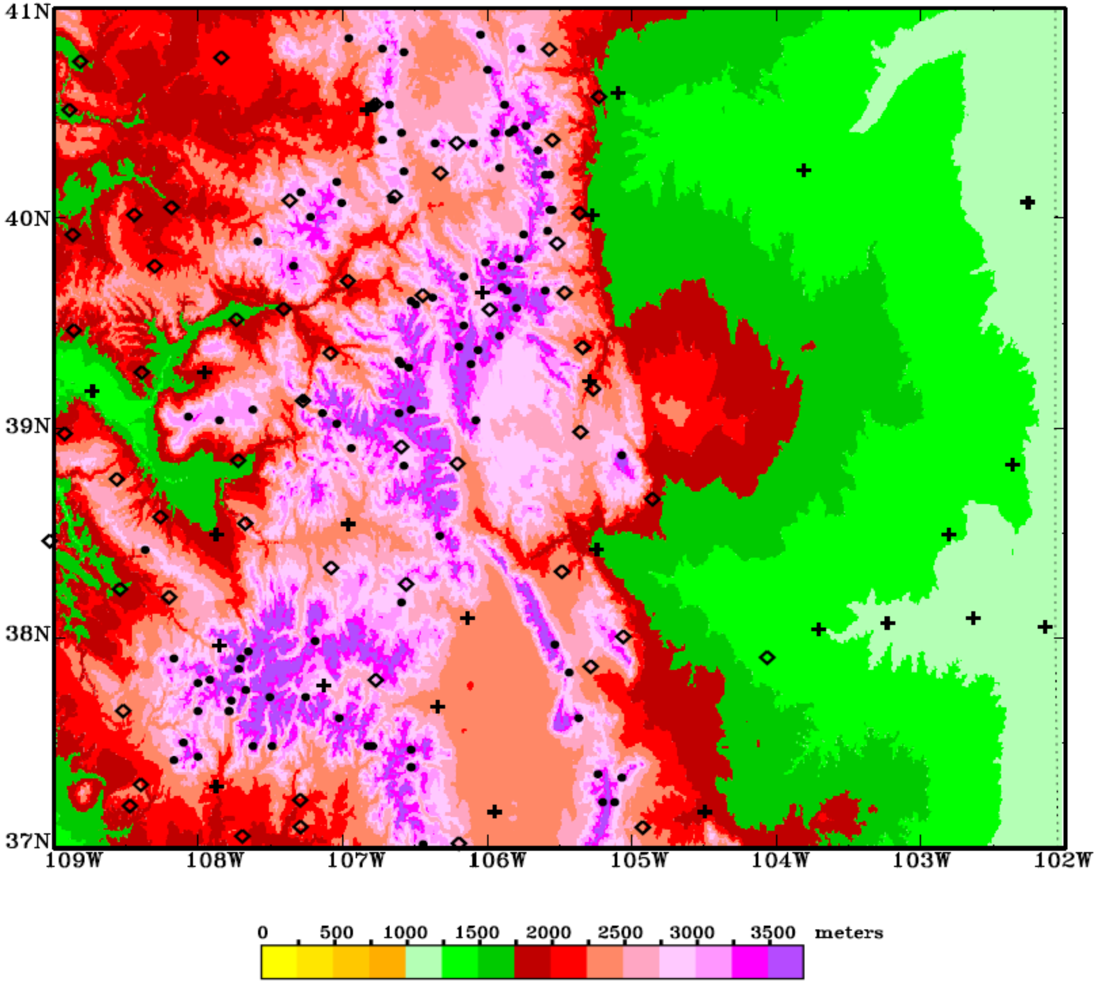
SNOTEL: dots
USHCN: pluses
RAWS: diamonds

USHCN: US Historical Climate Network
RAWS: Remote Automated Weather Stations

Site Numbers Available in Each State

	SNOTEL	USHCN	RAWS	TOTAL
AZ	15	19	69	103
CA	32	50	296	378
CO	99	25	60	184
ID	82	21	72	175
MT	90	35	77	202
NM	21	24	43	88
NV	27	12	46	85
OR	75	36	132	243
UT	87	38	54	179
WA	59	33	70	162
WY	82	26	37	145
Other			36	36
TOTAL	670	319	992	1981

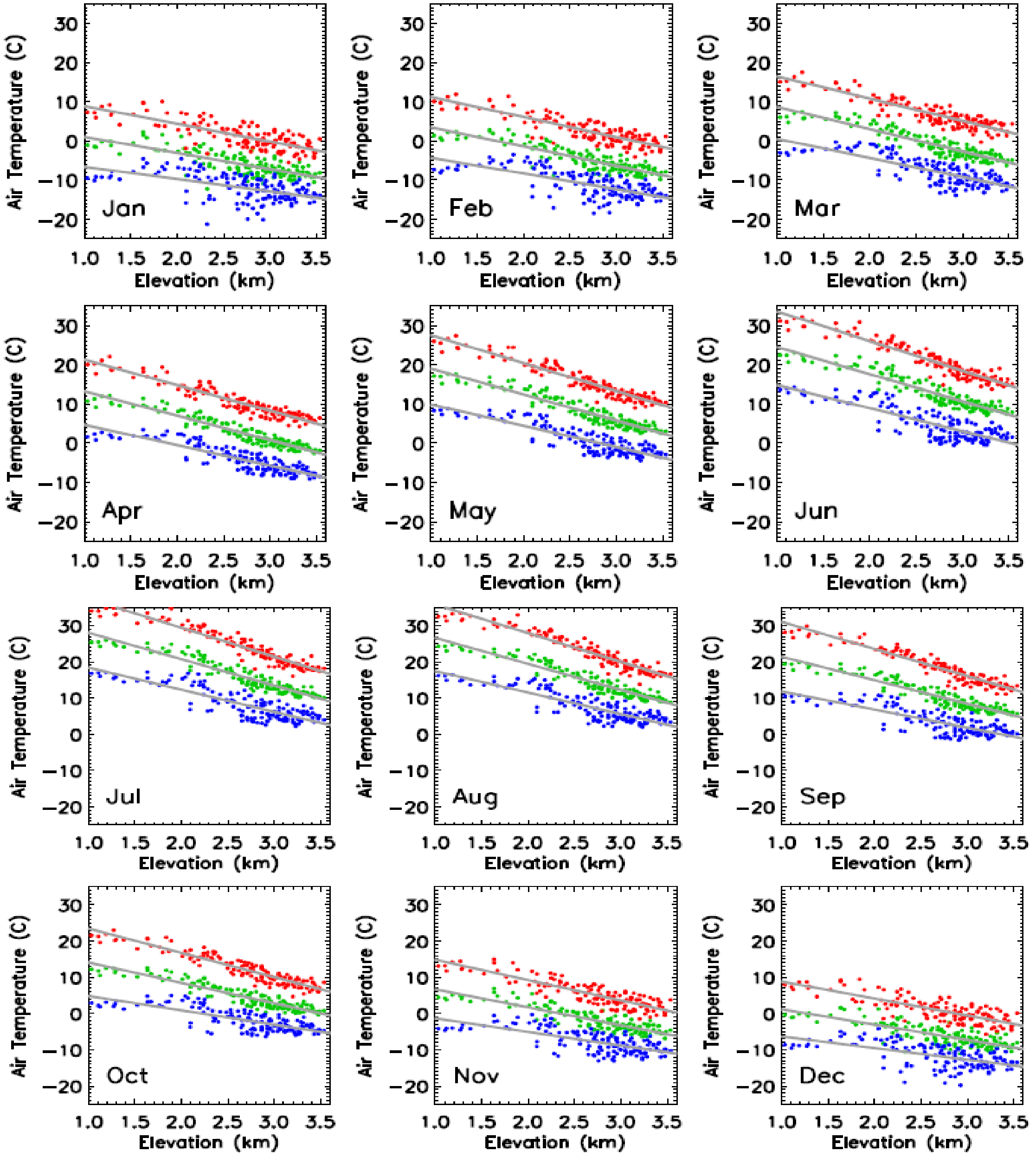
Colorado (184)



SNOTEL: dots
USHCN: pluses
RAWS: diamonds

For each month at each in-situ station, we compute the average of temperature separately for daily mean, daily maximum, and daily minimum air temperatures over a 20-yr period from 1991 to 2010, and plot the mean air temperature versus the elevation for each month.

Colorado (184)

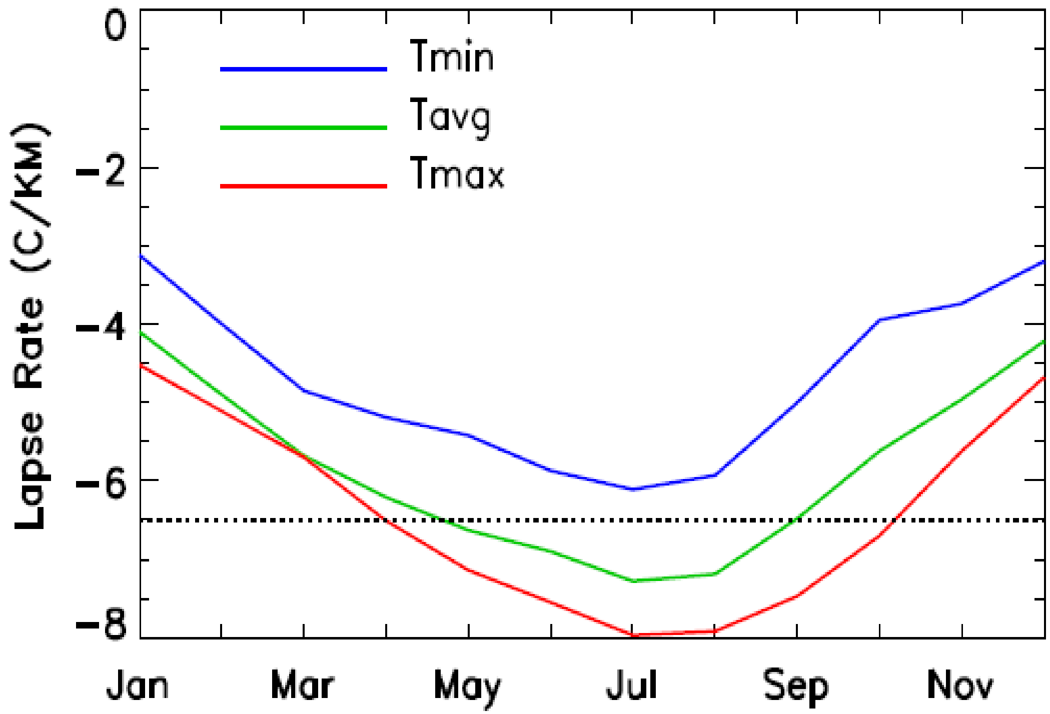


Red dots – Daily max Tair
Green dots –Daily mean Tair
Blue dots –Daily min Tair

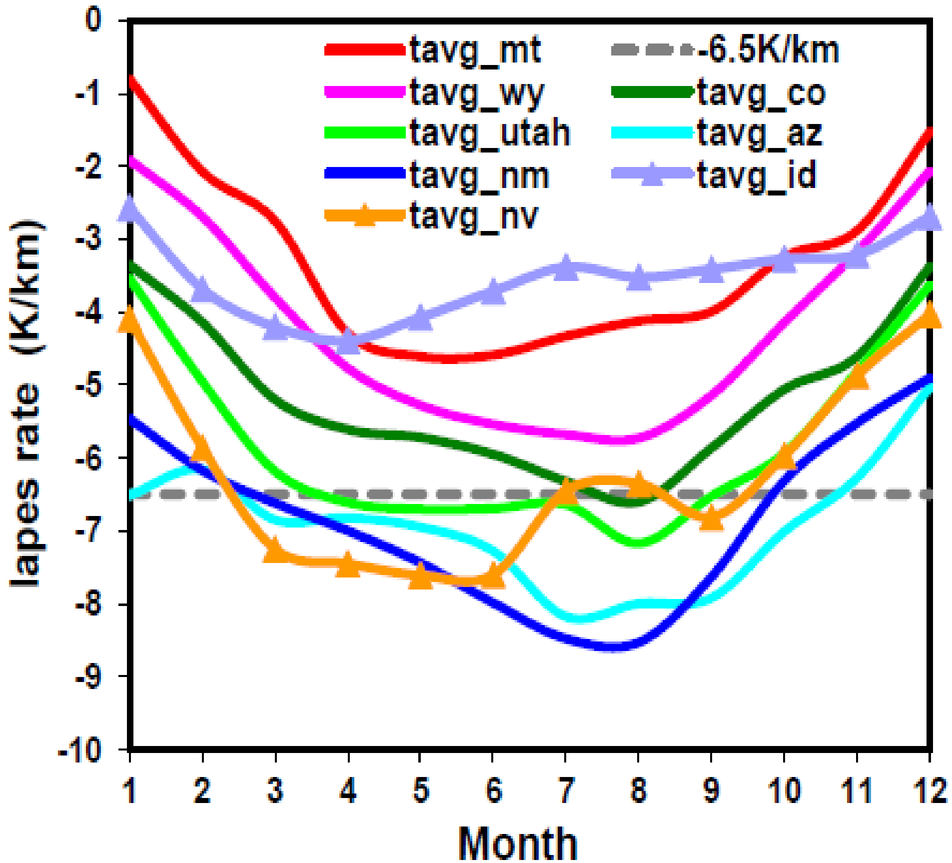
A linear regression fit is applied to the data based on a least squares approach, and the resulting regression slope yields the lapse rate value.

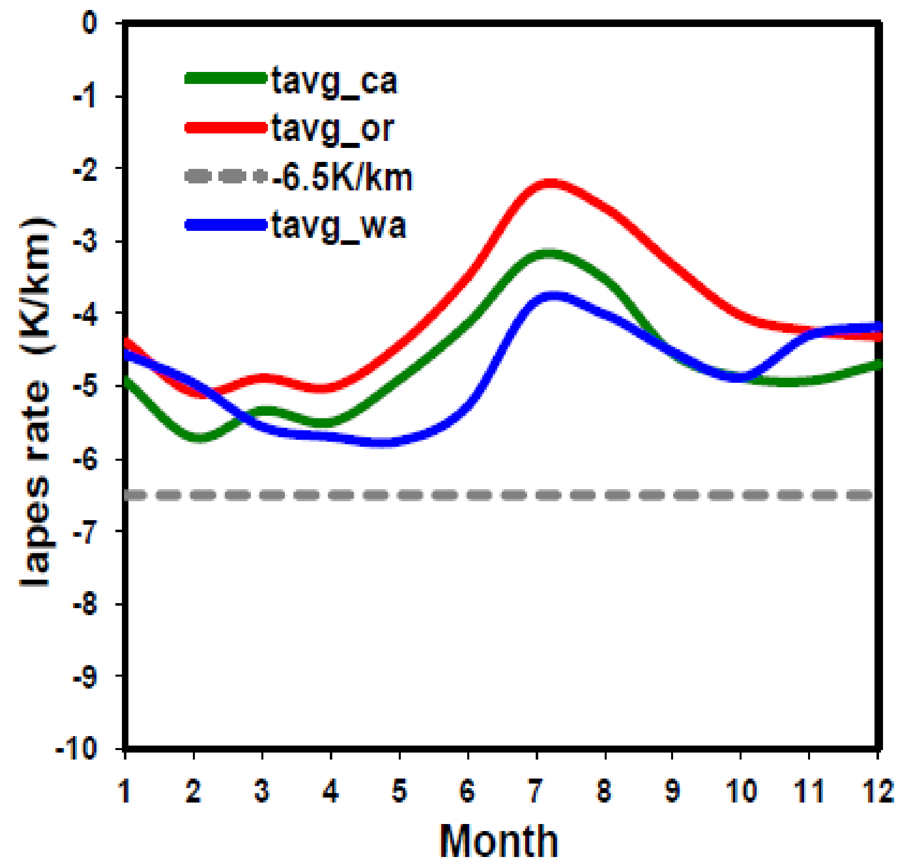
Colorado (184)

Month	Variable	T_0	γ	R	p-value
January	T_{avg}	3.3	-3.6	-0.535	0.000
	T_{max}	12.6	-4.32	-0.602	0.000
	T_{min}	-7.0	-2.14	-0.272	0.006
February	T_{avg}	6.82	-4.47	-0.676	0.000
	T_{max}	15.9	-5.01	-0.711	0.000
	T_{min}	-3.53	-3.09	-0.409	0.000
March	**T_{avg}**	**12.9**	**-5.26**	**-0.820**	**0.000**
	T_{max}	**22.0**	**-5.64**	**-0.812**	**0.000**
	T_{min}	**2.29**	**-4.00**	**-0.569**	**0.000**
April	**T_{avg}**	**18.0**	**-5.82**	**-0.891**	**0.000**
	T_{max}	**27.7**	**-6.47**	**-0.868**	**0.000**
	T_{min}	7.39	-4.51	-0.725	0.000
May	**T_{avg}**	**23.9**	**-6.16**	**-0.890**	**0.000**
	T_{max}	**34.0**	**-6.94**	**-0.900**	**0.000**
	T_{min}	13.0	-4.80	-0.620	0.000
June	**T_{avg}**	**29.1**	**-6.28**	**-0.872**	**0.000**
	T_{max}	**39.7**	**-7.18**	**-0.887**	**0.000**
	T_{min}	17.9	-5.12	-0.464	0.000
July	**T_{avg}**	**32.9**	**-6.62**	**-0.906**	**0.000**
	T_{max}	**43.3**	**-7.44**	**-0.916**	**0.000**
	T_{min}	21.5	-5.28	-0.520	0.000
August	**T_{avg}**	**31.7**	**-6.61**	**-0.905**	**0.000**
	T_{max}	**41.8**	**-7.43**	**-0.921**	**0.000**
	T_{min}	20.6	-5.18	-0.568	0.000
September	**T_{avg}**	**26.0**	**-5.96**	**-0.867**	**0.000**
	T_{max}	**37.2**	**-7.16**	**-0.892**	**0.000**
	T_{min}	14.1	-4.23	-0.482	0.000
October	**T_{avg}**	**18.2**	**-5.22**	**-0.826**	**0.000**
	T_{max}	**29.6**	**-6.59**	**-0.857**	**0.000**
	T_{min}	6.04	-3.18	-0.495	0.000
November	T_{avg}	10.2	-4.57	-0.714	0.000
	T_{max}	20.0	-5.52	-0.724	0.000
	T_{min}	-0.53	-2.91	-0.433	0.000
December	T_{avg}	3.94	-3.83	-0.543	0.000
	T_{max}	13.1	-4.59	-0.616	0.000
	T_{min}	-6.21	-2.34	-0.284	0.004

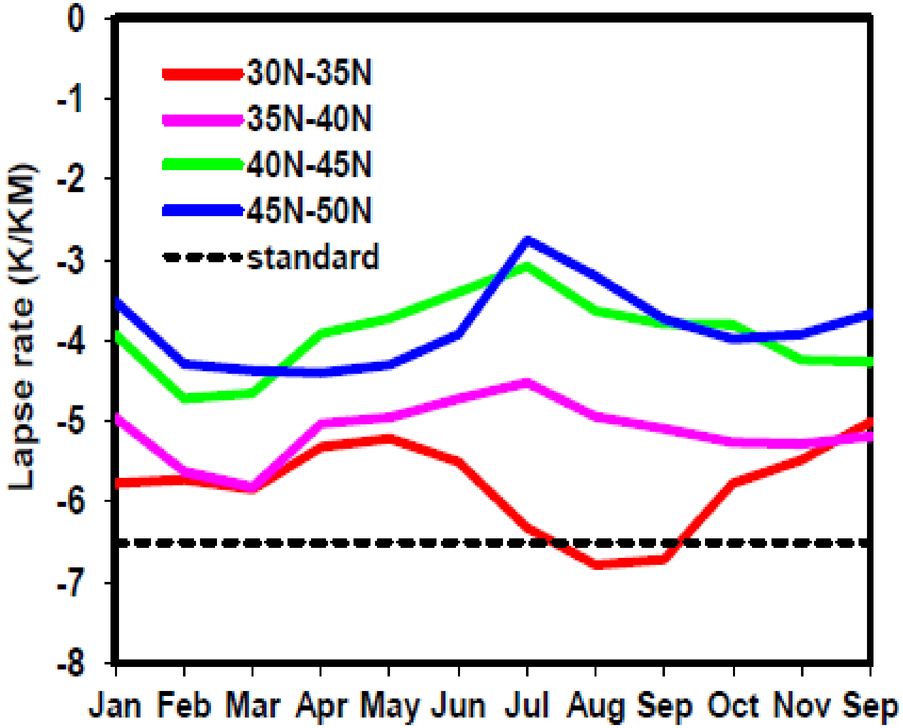


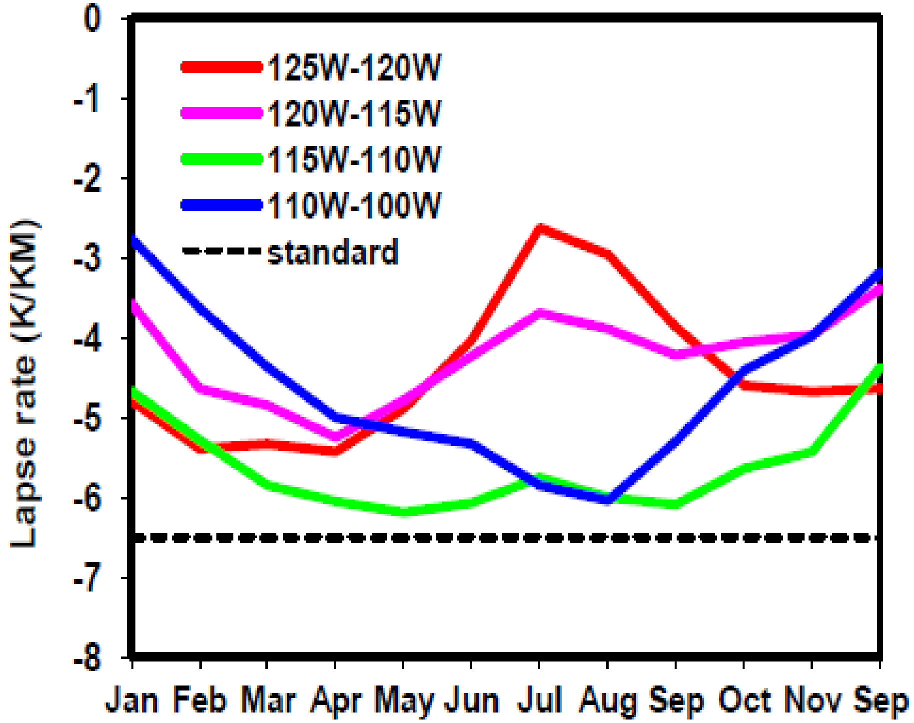
The regression equations are all statistically significant at a $p<0.01$ level, thus we are able to estimate statistically meaningful relationships between temperature and elevation.





Monthly lapse rate for each individual state in the western US derived from daily mean air temperature

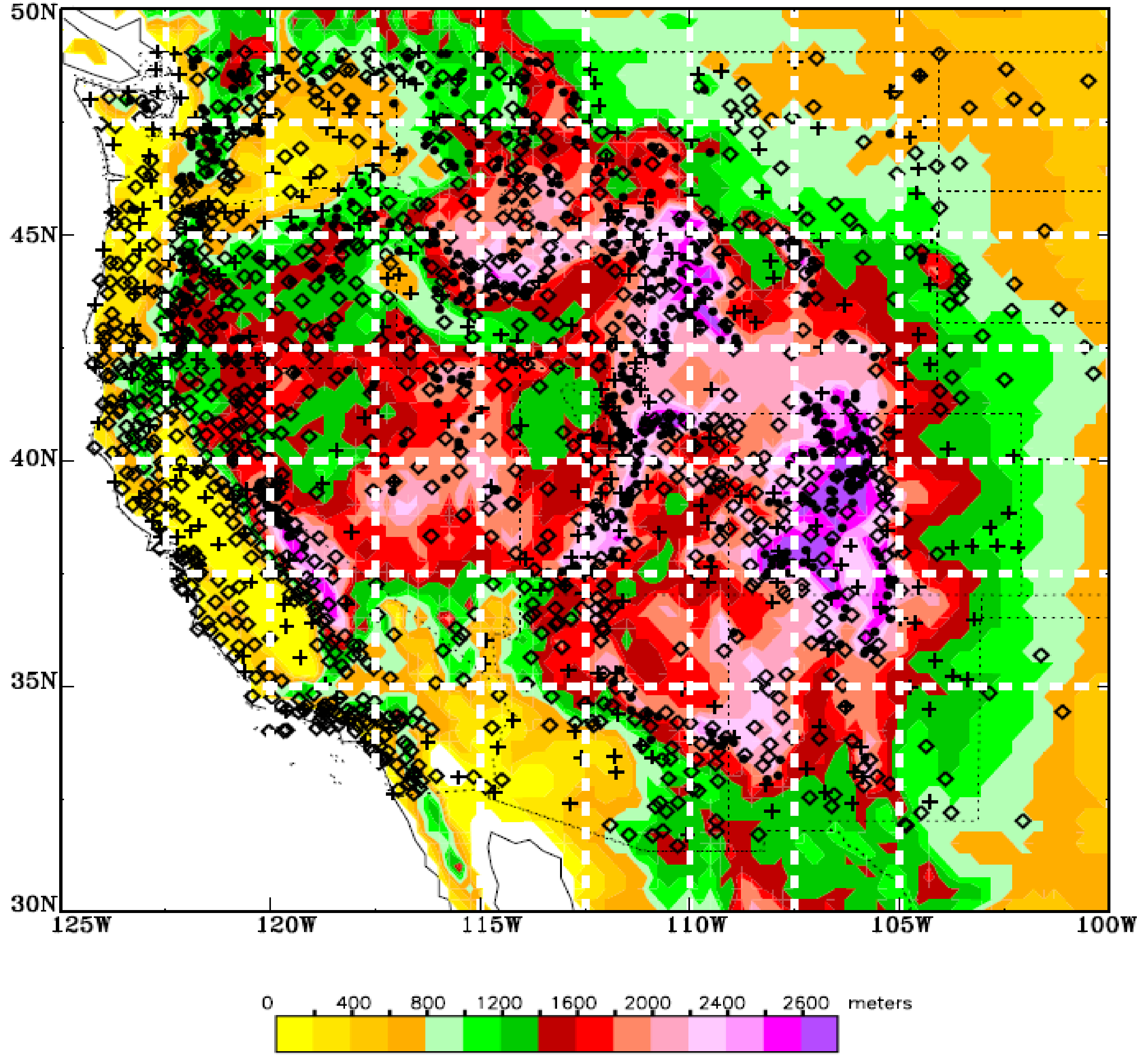




Monthly lapse rate for different latitude (left) and longitude bands (right).

Can we use air temperature as a proxy to quantitatively predict the variations of lapse rate?

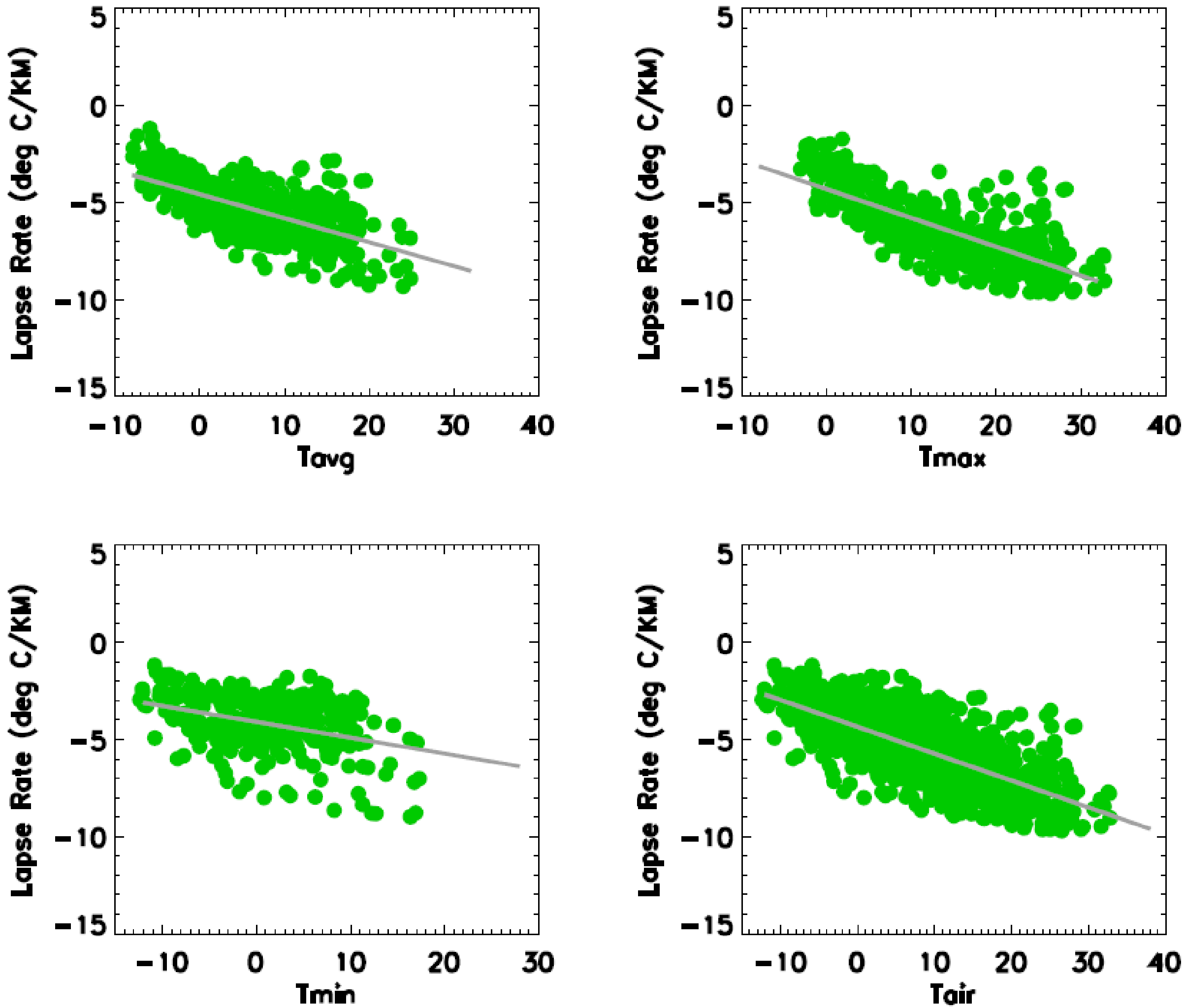
2.5deg By 2.5deg Boxes



DOTS: SNOTEL

PLUSES: USHCN

DIAMONDS: RAWS



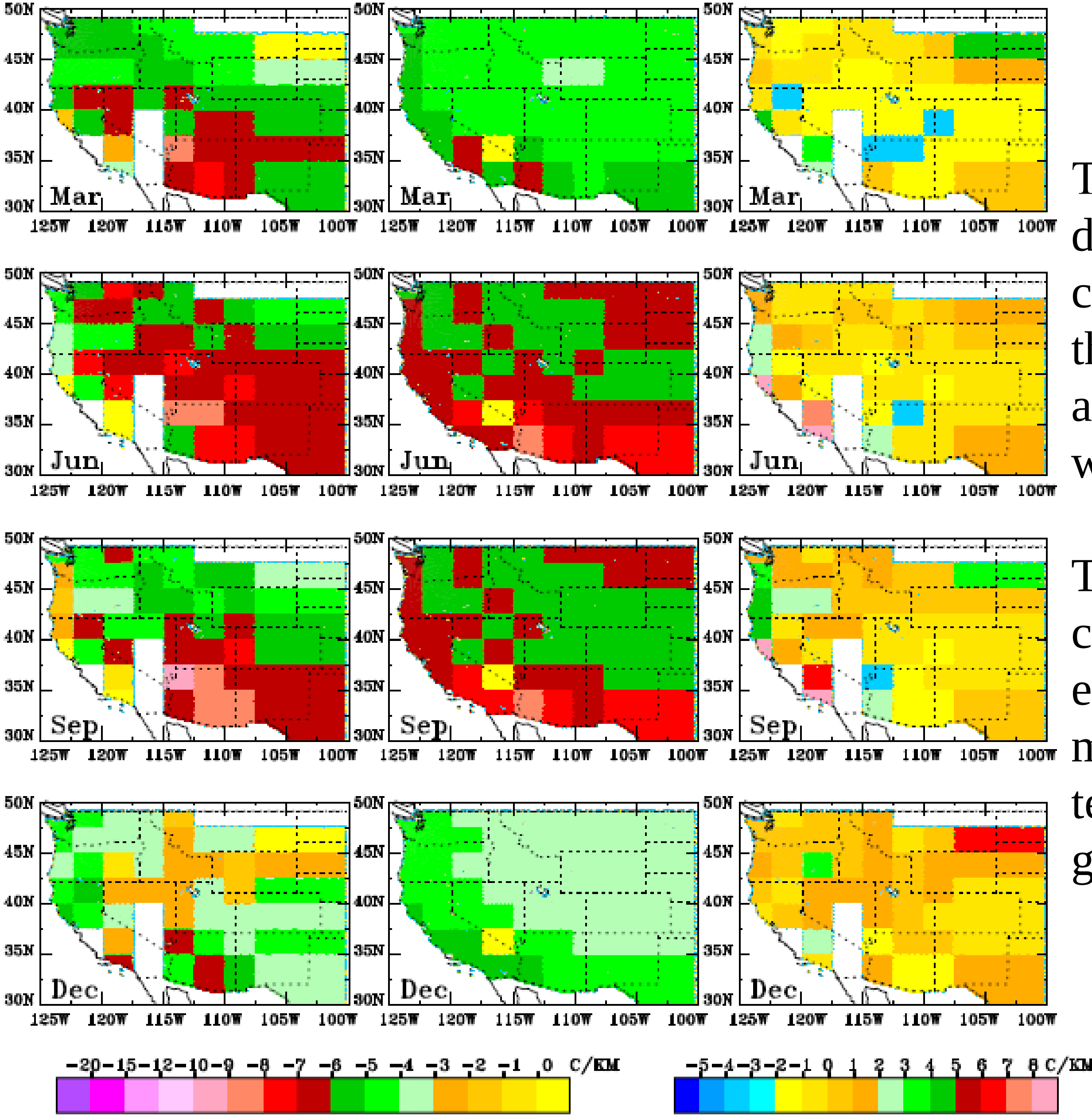
$$LR = a + b * \mathrm{Tair}$$

***LR*=Lapse Rate**

T_{air}	a	b	R	RMS
T_{avg}	-4.57	-0.12	-0.618	1.21
T_{max}	-4.31	-0.14	-0.738	1.13
T_{min}	-4.09	-0.08	-0.322	1.28
T_{avg}, T_{max}, T_{min}	**-4.34**	**-0.13**	**-0.712**	**1.24**

Verification using 2011 Data

“Observed” Predicted Difference



The “observed” lapse rate is derived by the ratio of the change in air temperature to the change in elevation among the in-situ stations within each grid box.

The predicted lapse rate is calculated from regression equation using in-situ based mean monthly air temperatures as input for each grid box.

Summary and Discussion

•Lapse rate magnitudes were found to increase as 2-meter air temperature increases.

•Air temperature is a good proxy for predicting the lapse rate, and the statistical linear regression equation is spatially and temporally independent, with air temperature as the only input variable.

•The approach can produce time- and space-varying lapse rates, and require minimal resources.

•When implementing in the downscaling software, this study will support real-time and retrospective land surface and hydrologic modeling activities.

•The current regression equation has been derived from a single temperature variable. We argue that other variables, such as the dew point, may show some impacts to the variation of lapse rate. Future work will study the impact of dew point to the lapse rate.